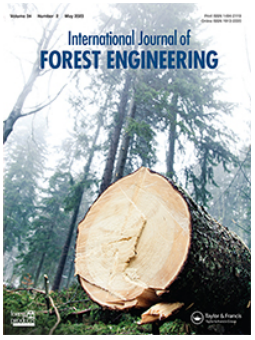

Taylor & Francis
Taylor & Francis Group

International Journal of Forest Engineering

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tife20

A framework for defining weights of decision makers in group decision-making, using consistency between different multicriteria weighting methods

Boško Blagojević, Eva-Maria Nordström & Ola Lindroos

To cite this article: Boško Blagojević, Eva-Maria Nordström & Ola Lindroos (2023) A framework for defining weights of decision makers in group decision-making, using consistency between different multicriteria weighting methods, International Journal of Forest Engineering, 34:2, 130-142, DOI: 10.1080/14942119.2023.2192774

To link to this article: https://doi.org/10.1080/14942119.2023.2192774

INTERNATIONAL JOURNAL OF FOREST ENGINEERING
2023, VOL. 34, NO. 2, 130–142
https://doi.org/10.1080/14942119.2023.2192774

A framework for defining weights of decision makers in group decision-making, using consistency between different multicriteria weighting methods

Boško Blagojević [a,b], Eva-Maria Nordström [c], and Ola Lindroos [a]

[a]Department of Forest Biomaterials and Technology, Swedish University of Agricultural Sciences, Umeå, Sweden; [b]Faculty of Agriculture, University of Novi Sad, Novi Sad, Serbia; [c]Department of Forest Resource Management, Swedish University of Agricultural Sciences, Umeå, Sweden

ABSTRACT

Most forest operations are complex problems that require the weights of relevant criteria – representing trade-offs between various economic, ecological, and social aspects of the problem – to be defined. Usually this is done by using multicriteria weighting method(s) in a group (participatory) context in order to include different opinions and to minimize risk of poor individual judgments. Furthermore, in group decision-making, the weights of decision makers (DMs) must be defined. However, no consensus exists on the best way to determine related weights assigned to DMs. For that purpose, we propose the consistency-based group decision-making framework (CGDF), which uses the expertise of a DM to weight the responses of the DM when deriving an overall group decision. The novel part of CGDF is the inter-weights consistency method (ICM) for evaluating the expertise of a DM based on the consistency of the weights the DM assigns to different criteria using different multicriteria weighting methods. We demonstrate the utility of ICM and CGDF by applying them to a decision-making problem from Swedish forest operations – defining weights of criteria relevant for designing the machine-trail network for driving in the forest terrain.

ARTICLE HISTORY
Received 2 September 2022
Accepted 15 March 2023

KEYWORDS
Multicriteria decision analysis; method development; expertise of decision makers; consistency; extraction; forwarding

Introduction

In the past, forestry was mainly concerned with maximizing profit, so the main considerations focused on economical efficiency. However, nowadays forest operations are expected to consider all dimensions of sustainability, and therefore complex problems require the balancing of trade-offs between various economic, ecological, and social aspects of the problem (Marchi et al. 2018). Hence, there is a need of multicriteria decision analysis (MCDA) methods for such balancing, which to a certain extent are used in the planning of forest operations (Blagojevic et al. 2019). In the MCDA methods, criteria are defined and given weights to computationally find a solution. Criteria are chosen to represent the values of interest, that are being considered required to balance. Those are normally rather straightforward to define, compared to the process to define how to weight their importance relative to each other.

The most common way to define the weights assigned to criteria is to elicit preference values (subjective judgments) from experts or decision makers (DMs). Usually this is done in a group (participatory) context in order to include different opinions and to minimize risk of poor individual judgments.

There are several multicriteria weighting methods for deriving weights from preference statements, the most common being direct point allocation (DIRECT), simple multi-attribute rating technique (SMART) (Edwards 1977; von Winterfeldt and Edwards 1986), analytic hierarchy process (AHP) (Saaty 1980), trade-off (Keeney and Raiffa 1976) and SWING (von Winterfeldt and Edwards 1986). The last two methods explicitly incorporate criteria ranges in the elicitation questions, meaning that minimum and maximum levels for each criterion need to be known before interviews start. Although the impact of elicitation methods on weights is undisputed, there does not yet seem to be any consensus about the most valid method (Lienert et al. 2016).

Besides the weighting method, quality of outcome depends to a great extent on two other aspects: (i) the size and composition of the group of DMs, and (ii) the expertise of DMs and the corresponding quality of their judgment (Kontic 2000; Noble 2004). The literature suggests there is no standard procedure for defining the former aspect of the problem setting – rather, it is case specific. In contrast, there are many approaches for determining the expertise (henceforth referred to as "weight") of a DM: see, for example, the detailed review by Koksalmis and Kabak (2019). We now describe two of the main approaches.

Cooke's classical approach (Cooke 1991) is, according to French (2011), the most frequently applied method in the validity or knowledge-based approach, in which the weights assigned to DMs are based on their ability to perform a relevant task. As a result many DMs may be discarded (having zero weights) from the subsequent decision-making process (French 2011). When there is some objective, an external criterion exists (such as correct answer to question) then the validity-based approach can be reasonable and straightforward – expertise of DMs will be determined easily by comparing their judgments with the correct answers (Weiss and Shanteau 2003). The main problem with this approach is that

CONTACT Boško Blagojević bosko.blagojevic@polj.edu.rs Department of Water Management, Faculty of Agriculture, University of Novi Sad, Trg D.Obradovica, 8, Novi Sad 21000, Serbia

This article has been republished with minor changes. These changes do not impact the academic content of the article.

experts are usually needed in precisely those domains where no correct answers exist (Gigerenzer and Goldstein 1996).

The second way of defining expertise of DMs is based on characteristics that experts would be expected to have (Shanteau et al. 2002). Such characteristics might include: (1) experience – number of years of relevant job experience; (2) certification – in many professions, individuals receive some form of title or qualification in recognition of their skills and competencies; (3) social acclamation – professionals are asked whom they consider to be an expert; (4) consistency – expert´s judgments should be internally consistent (Einhorn 1972, 1974); (5) consensus – experts in a given field should agree with each other (Einhorn 1972, 1974); (6) discrimination ability – ability to make fine discriminations between similar but not equivalent cases (Hammond 1996); (7) behavioral characteristics – experts share many common characteristics such as self-confidence, creativity, perceptiveness, communication skills and stress tolerance (Abdolmohammadi and Shanteau 1992); and (8) knowledge tests – experts are identified based on tests of factual knowledge. Although these characteristics have been useful in identifying experts, each of them has one or more serious flaws (Shanteau et al. 2002). As a solution for measuring expertise, Weiss and Shanteau (2003) propose the CWS (Cochran–Weiss–Shanteau) index which represents the ratio of discrimination ability over inconsistency. This means that an expert – like a good measuring instrument – must be both discriminating and consistent. The main idea behind this method is that it can be easy for lay people (nonexperts) to display discrimination or consistency, but hard to do both. Although this may be true in many cases, it is also important to highlight two important shortcomings of this method:

- Designing a questionnaire that can calculate discriminatory ability is a very complicated task for the decision analyst (Weiss and Shanteau 2003).
- Answering the questionnaire may be time-consuming for DMs – instead of giving only answers related to analyzing decision problems, they need to invest additional time to answer consistency and discriminatory questions.

Given that no consensus exists regarding the most valid elicitation method (for criteria weighting and evaluation of expertise) and that existing methods for defining DMs' weights have many limitations, this paper presents the consistency-based group decision-making framework (CGDF). An integral part of the framework is a novel method for defining the weights assigned to DMs – the inter-weights consistency method (ICM). This paper has two main objectives. The first is to present a group decision-making framework that is neutral with respect to multicriteria weighting methods, thereby enabling a DM to use more than one weighting method and then have the freedom to select the method that best reflects their individual preferences. The second objective is to present a novel method for assigning weights to DMs, one that is easy to use and is not time-consuming. ICM is based on the consistency between results provided by DMs using different weighting methods. It has its origins in the work of Weiss and Shanteau (2003), but is less complicated and time-consuming to use than their CWS index. Although consistency is not a guarantee that someone is an expert, it is a good indicator that a DM has a clear opinion or a clear understanding about the problem under consideration – at least in relation to other DMs. The application of CGDF and ICM is demonstrated in a forestry related decision-making problem. As a case, weights were defined for criteria included for designing machine-trail networks for logging operations. Recently, computational multi-objective methods for designing these networks have been proposed (e.g. Hosseini et al. 2018; Holmström et al. 2022), all of which require the weights of relevant criteria.

The focus of this study was on how to defining weights of decision makers in group decision-making situations, but to assist in applying the results into solving real-life MCDA problems the steps for doing so are described in Appendix A.

Case context

Harvesting and moving the harvested trees to roadside for transportation are significant forestry operations, in the sense that large amounts of resources are required, large monetary values are created, and ecological and social harm may be caused by these activities (Blagojevic et al. 2019). In the Nordic countries, for example, these operations are usually performed by cut-to-length (CTL) machines. The harvester fells and processes trees into logs of various assortments (such as various kinds of saw-logs and pulp-logs). The harvester then moves the logs to the side so that it can advance (and harvest more trees) without damaging them. This results in a "machine-trail network" of paths (or "strip roads") cleared of trees and logs. A forwarder then travels down the machine trails collecting logs and transporting them to roadside landings. The activities of this heavy machinery on wet and soft ground may cause soil compaction, which can lead to considerable long-term impact in biological activity (Heralt 2002; Horn et al. 2007) and if soil is moved and ruts are created, surface water run-off may result in leakage of sediments and pollutants such as mercury into streams (Porvari et al. 2003; Eliasson 2005). There are also economic reasons for avoiding soil damage. Driving on wet and soft ground reduces speed and/or increases fuel consumption, and a machine that becomes stuck in mud results both in severe time losses and possible machine damage (Hosseini et al. 2018).

Determining an optimal machine-trail network is a complex problem that requires understanding of how forestry machines will operate on the terrain as well as the trade-offs between various criteria – representing economic, social and ecological aspects (Hosseini et al. 2018). Machine-trail networks are currently designed manually based on intuitive decisions about the importance, correlations, and effects of many potentially conflicting criteria. However, computational methods for designing these networks have been proposed (Hosseini et al. 2018; Holmström et al. 2022), all of which require the weights of relevant criteria.

Consistency-based group decision-making framework

Consistency – which can be also called intra-individual reliability (Weiss and Shanteau 2003) – is a statistical measure of the extent to which an individual's preferences are logical and based on expertise rather than randomly chosen (Noble 2004). There are three main schools of thought regarding the formation and consistency (existence) of preferences. The economics school of thought is based on the assumption that DMs have existing preferences and express those preferences during the elicitation process. The second is based on the view that people's preferences are often constructed during the process of elicitation (Slovic 1995). According to Lichtenstein and Slovic (2006) in many situations we do not really know our real preferences so we construct them during the elicitation process. The third school of thought – which underpins CGDF and ICM – is based on the idea that inexperienced DMs construct their preferences during the elicitation (decision-making) process, while DMs with experience in the problem domain have more consistent (or stable) preferences (Hoeffler and Ariely 1999). For example, take the comparison between a soon-to-be and an experienced parent when evaluating different baby strollers and their respective attributes, which showed that the experienced parent has consolidated their preferences (Hoeffler and Ariely 1999). Although experience is not the same as expertise, there is undoubtedly a positive relationship between them (Shanteau et al. 2002).

Consistency can be measured using a single weighting method (e.g. in AHP method consistency index is used to measure consistency of individual judgments), over time, by repeatedly collecting preferences from the same DMs using the same weighting method (e.g. Lienert et al. 2016). It can also be measured by using different weighting methods. According to Einhorn (1972, 1974) consistency is a necessary condition for expertise – because an expert could hardly behave randomly. However, inconsistency in a DM's responses may not be just because of lack of expertise. It could be that the DM did not understand the problem and related question(s), misunderstood the weighting method(s), did not have experience of using weighting method(s), was not fully concentrating, was tired, or just changed preferences during the elicitation phase. Whatever the reason, inconsistency is an indicator that the DM may be relatively unreliable. Therefore, a key-idea in the CGDF and ICM is that the weights of less consistent DMs should have lower impact on group decisions than those who are more consistent.

ICM, which forms the core of CGDF, uses the Euclidean distance metric to calculate inter-weights consistency, given by equation (1):

$$ED_j = \left[\frac{\sum_{i=1}^{n}\sum_{k=1}^{p}\left(w_{ij}^{k} - \overline{w_{ij}}\right)^2}{p-1}\right]^{\frac{1}{2}}, j = 1, \ldots, m \quad (1)$$

where m is the number of decision makers; n is the number of criteria, p is the number of weighting methods used; ED_j is the inter-weights consistency of decision maker j, w_{ij}^{k} is the weight assigned to criterion i by decision maker j using weighting method k, and $\overline{w_{ij}} = \frac{1}{p}\sum_{k=1}^{p} w_{ij}^{k}$. It should be noted that other Lebesgue spaces (L^p) metrics (Manhattan distance, for example) could be used to define inter-weights consistency, but Euclidean distance is more often used in relevant literature to measure consistency (Blagojevic et al. 2016).

Obviously, if ED_j equals 0, then DM j is perfectly consistent, meaning that DM j assigned the same weight to every criterion for each weighting method. Otherwise, the smaller the value of the ED_j the greater the inter-weights consistency. In addition, ED should be interpreted only in relative and not absolute terms (i.e. it can be only used to say which of two experts is more consistent for that particular decision-making problem), otherwise it is necessary to divide ED by the number of criteria to make it comparable with EDs from other decision-making problems. Then, the proposed CGDF and ICM are defined in the following steps:

Begin CGDF:

Step 1. Individual weights w_{ij}^{k} are obtained from every DM using p weighting methods ($k = 1, \ldots, p$) and $p \geq 2$. The order in which preferences of DMs are collected (order of usage of weighting methods) is not prescribed by CGDF. This order and p are defined by the decision analyst according to the characteristics of the particular decision-making problem.

Step 2. The results of the different weighting methods are shown to the DM who chooses the set of weights (w_{ij}^{select}) that the DM considers represents their preferences in the most accurate way.

Begin ICM:

Step 3. For every DM, average weights of criteria from all used weighting methods ($\overline{w_{ij}}$) are computed.

Step 4. ED_j and $1/ED_j$are computed for DM j, $j = 1, \ldots, m$. If $ED_j = 0$ (although this can happen only in theory) then the decision analyst selects a fixed, positive value that is close to 0.

Step 5. The weight assigned to a DM j is derived using equation (2):

$$\alpha_j = \frac{(ED_j)^{-1}}{\sum_{j=1}^{m}(ED_j)^{-1}} \quad (2)$$

Note that $\sum_{j=1}^{m}\alpha_j = 1$.

End ICM

Step 6. Finally, the group weight of each criterion i (w_i^{gr}) is calculated by summing the products of the weight selected by the DM j for criterion i and the weight assigned to DM j by ICM, equation (3):

$$w_i^{gr} = \sum_{j=1}^{m}\left(w_{ij}^{select} \times \alpha_j\right), i = 1, \ldots, n \quad (3)$$

End CGDF

As Step 4 indicates, we have to introduce a correction in the case of a DM having perfect consistency (that is $ED_j = 0$ for some j). However, such a situation only arises if the DM allocates equal weights to each criterion using each weighting method. Although this is possible in principle and requires no cognitive effort on the part of the DM, it is hard to see what a DM would achieve by doing that. This strategy may be only beneficial if the DM truly believes that all criteria should have equal weights. Otherwise, this strategy is unrepresentative of the DM's true position and interests, and means that the DM's real preferences are not taken into consideration in the group decision-making process.

Alternatively, using CGDF and ICM have several desirable qualities:

- Simplicity – it is easy for the decision analyst to prepare a questionnaire because only questions related to the presented problem will be asked (it is not necessary to have additional questions).
- Effectiveness – using several weighting methods allows a DM to select a method that best expresses their preferences and serves as a mechanism for calculating the consistency of a DM.
- Efficiency – the presented methodology is relatively quick to implement and therefore suitable when there are many DMs and time constraints.

Materials and methods

Selected criteria relevant for designing the machine-trail network for driving in the forest terrain

For the sake of this study and to progress the work on machine-trail network design, five criteria were identified based on literature reviews and our personal views. The selected criteria were:

- ECON – to minimize financial costs (all possible harvesting and forwarding costs: fuel consumption, operator's salaries, maintenance, etc.);
- SOIL – to minimize risk of soil damage – compaction and rutting (proportional to weight of the machines, number of the machine passages, soil moisture, etc.);
- CO2 - to minimize CO_2 emissions;
- ERG – to minimize the tilt and roll of the machines (due to ergonomic reasons); and
- GROW – to minimize the area with roads (i.e. to maximize the stand's capacity to grow trees).

Methods used for criteria weighting

As noted in the introduction, there are many methods to elicit criteria weights. However, it is important to notice that for the real-life multicriteria decision-making problems it is necessary to have the ranges of the selected criteria, i.e. weights have to be defined in relation to ranges of criteria.

This study used DIRECT, AHP, and SMART which are described in general terms below.

In the DIRECT method, the DM allocates points to each criterion. For example, the DM is asked to distribute 100 points among the criteria. The DM is also allowed to distribute more (or less) than 100 points. Then the points are summed, and the final weights are the points of each criterion divided by the sum.

In the AHP method (Saaty 1980), the DM compares all n criteria in pairs ($n(n-1)/2$ comparisons in total), and assigns a value a_{ij} from the scale given in Table 1 representing the relative importance of criterion i over criterion j.

These values are used to define a matrix A in which $a_{ii} = 1$ for all i and $a_{ij} = 1/a_{ji}$ for all i and j. The weights of the criteria are then calculated using one of exiting prioritization methods. In this study we used the logarithmic least squares (LLS) prioritization method (Crawford and Williams 1985), where the weights of criteria are the normalized geometric means of the rows of matrix A (equation (4)):

$$w_i = \frac{\sqrt[n]{\prod_{j=1}^{n} a_{ij}}}{\sum_{i=1}^{n}\left(\sqrt[n]{\prod_{j=1}^{n} a_{ij}}\right)} \tag{4}$$

SMART (Edwards 1977; von Winterfeldt and Edwards 1986) is a decision-support method developed in the field of multi-attribute utility theory (Kangas et al. 2015). When using SMART, the weights are elicited in two steps: (1) the DM ranks all criteria; and (2) the DM begins by assigning 10 points to the least important (lowest ranked) criterion, and then assigns points greater than or equal to 10 (with no upper limit) to the other criteria (Pöyhönen and Hämäläinen 2001). Then the weight of a criterion is defined to be the points assigned to it divided by the total points assigned to all criteria (like the DIRECT method).

Data gathering

Criteria weights were gathered from a group of 18 forestry experts (DMs), all from Sweden, in individual, face-to-face interviews conducted by the same decision analyst in order to obtain independent answers that had not been influenced by the opinions of other members of the group. The interviews were held during May and June 2018 and lasted around 15 to 30 min per person. The group comprised managers from forestry companies, contractor, forestry PhD students and forestry university researchers.

During the interviews, the problem, criteria, methods and questions were explained by the decision analyst. The DMs were also provided with a two-page questionnaire (Figure B1 in Appendix B). The first page contained the problem setting, the selected criteria and space to assign weights to the criteria using the DIRECT method (Q1). On the second page, DMs defined weights using AHP (Q2) and SMART (Q3), expressed an opinion about the relevance of the criteria to the problem (Q4), and suggested other criteria (Q5). The results of all

Table 1. Saaty's importance scale.

Definition	Importance
Equal importance	1
Weak dominance	3
Strong dominance	5
Demonstrated dominance	7
Absolute dominance	9
Intermediate values	(2, 4, 6, 8)

Table 2. Description of group weighting of criteria.

Group decision	Weights of criteria obtained with:	Method of assigning weights to DMs
GD1	DIRECT	Equal weights are assigned to DMs
GD2	DIRECT	ICM weights are assigned to DMs
GD3	AHP	Equal weights are assigned to DMs
GD4	AHP	ICM weights are assigned to DMs
GD5	SMART	Equal weights are assigned to DMs
GD6	SMART	ICM weights are assigned to DMs
GD7	Selected method by DM	Equal weights are assigned to DMs
CGDF	Selected method by DM	ICM weights are assigned to DMs

three weighting methods were shown to DMs and then they orally stated which of the three weighting methods they preferred using for the criteria weighting.

Comparing group weighting of criteria

For the presented case-study, the group weighting of criteria or just group decisions (GDs) are made from combinations of two sets of weights assigned to DMs (equal and derived with ICM) and four sets of individual criteria weights (obtained with DIRECT, AHP, SMART, and with selected weighting method). This is eight GDs in total and their descriptions are given in Table 2. In four of them the weights assigned to DMs are derived using ICM and one GD represents the value computed using CGDF. The main goal was to compare GDs where weights assigned to DMs were equal with those where weights assigned to DMs were derived with ICM.

Results

Table B1 in Appendix B presents the full results obtained from the questionnaires and the corresponding *ED*s. In Appendix A, the procedure for how to apply the weights in a real-life MCDA situation is described.

The weights assigned to a particular criterion varied considerably, as shown in Table 3. Most DMs had a tendency to give round numbers to weights with the DIRECT method (see Table B1 in Appendix B). Extreme weights were given only with AHP and DIRECT, but not with the SMART method (Table 3).

Table 4 shows weights of criteria for the weighting method selected by each DM and the weight assigned to each DM using ICM. The SMART method was selected by eight DMs, AHP by seven and DIRECT by three.

The weights assigned to DMs using ICM ranged from 0.0260 (DM11) to 0.1268 (DM12) (Table 4), both DMs being forestry university researchers (see Table B1 in Appendix B). Table 5 shows the differences between these two DMs. Notice that ICM accounted for the differences in the weights assigned by these DMs by assigning a weight to DM12 that is considerably more than would be assigned if all DMs were treated equally (i.e. one-eighteenth or approximately 0.0555) and considerably less to DM11.

Finally, Table 6 presents the eight GDs. Ranges for the group criteria weights were quite narrow, irrespective of the

Table 3. Extreme weights assigned to each criterion.

Criteria	Minimum weight	Decision maker-method	Maximum weight	Decision maker-method
ECON	0.080	DM18-AHP	0.600	DM7, 10, 13, 15-DIRECT
SOIL	0.049	DM5-AHP	0.475	DM14-AHP
CO2	0.000	DM3, 10, 14, 15, 16-DIRECT	0.300	DM5-DIRECT
ERG	0.000	DM10, 15, 16-DIRECT	0.527	DM11-AHP
GROW	0.000	DM10-DIRECT	0.474	DM17-AHP

Table 4. Individual weights of criteria obtained with selected weighting method and weights assigned to DMs using ICM.

		Criteria weights					
DMs	Methods	ECON	SOIL	CO2	ERG	GROW	Weights of DMs
DM1	SMART	0.264	0.236	0.167	0.139	0.194	0.0345
DM2	AHP	0.317	0.460	0.032	0.072	0.119	0.0679
DM3	SMART	0.235	0.294	0.059	0.265	0.147	0.0616
DM4	AHP	0.235	0.094	0.098	0.519	0.054	0.0593
DM5	SMART	0.526	0.053	0.132	0.263	0.026	0.0324
DM6	SMART	0.469	0.250	0.125	0.125	0.031	0.0309
DM7	AHP	0.596	0.122	0.043	0.176	0.063	0.0462
DM8	SMART	0.500	0.250	0.036	0.071	0.143	0.0461
DM9	DIRECT	0.400	0.100	0.250	0.100	0.150	0.0614
DM10	DIRECT	0.600	0.400	0.000	0.000	0.000	0.0279
DM11	SMART	0.306	0.222	0.167	0.278	0.028	0.0260[a]
DM12	AHP	0.362	0.175	0.070	0.054	0.338	0.1268[b]
DM13	AHP	0.486	0.287	0.032	0.077	0.117	0.0595
DM14	DIRECT	0.300	0.300	0.000	0.100	0.300	0.0494
DM15	SMART	0.400	0.320	0.040	0.040	0.200	0.0440
DM16	SMART	0.213	0.426	0.021	0.021	0.319	0.0946
DM17	AHP	0.180	0.221	0.084	0.040	0.474	0.0846
DM18	AHP	0.080	0.088	0.037	0.521	0.274	0.0470

[a]Minimal weight of DM; [b]maximal weight of DM.

Table 5. Weights and ranks of criteria obtained with all weighting methods for DMs with lowest (DM11) and highest weight (DM12).

DMs	Methods	ECON	SOIL	CO2	ERG	GROW
DM11	DIRECT	0.265 (1)	0.206 (3)	0.235 (2)	0.147 (4–5)	0.147 (4–5)
	AHP	0.239 (2)	0.120 (3)	0.071 (4)	0.527 (1)	0.043 (5)
	SMART	0.306 (1)	0.222 (3)	0.167 (4)	0.278 (2)	0.028 (5)
DM12	DIRECT	0.333 (1–2)	0.222 (3)	0.056 (4–5)	0.056 (4–5)	0.333 (1–2)
	AHP	0.362 (1)	0.175 (3)	0.070 (4)	0.054 (5)	0.338 (2)
	SMART	0.316 (1–2)	0.211 (3)	0.053 (5)	0.105 (4)	0.316 (1–2)

Table 6. Weights assigned to criteria by group decisions.

			Weights of criteria						
Group decision	Method	Weights of DMs	ECON	SOIL	CO2	ERG	GROW	Max-min	SD
GD1	DIRECT	Equal	0.354	0.230[a]	0.108[b]	0.136	0.169	0.246	0.098
GD2		ICM	0.338	0.237	0.096	0.125[a]	0.201	0.242	0.096
GD3	AHP	Equal	0.354	0.241	0.065[a]	0.176[b]	0.164[a]	0.289	0.107
GD4		ICM	0.326	0.250	0.066	0.152	0.206[b]	0.260	0.098
GD5	SMART	Equal	0.335	0.245	0.097	0.155	0.169	0.238	0.092
GD6		ICM	0.317[a]	0.252[b]	0.088	0.141	0.201	0.229	0.090
GD7	Selected	Equal	0.359[b]	0.239	0.077	0.159	0.165	0.282	0.106
CGDF		ICM	0.337	0.244	0.072	0.142	0.205	0.265	0.101

In a particular column, [a]represents the minimum weight for the criterion, and [b]is the maximum weight.

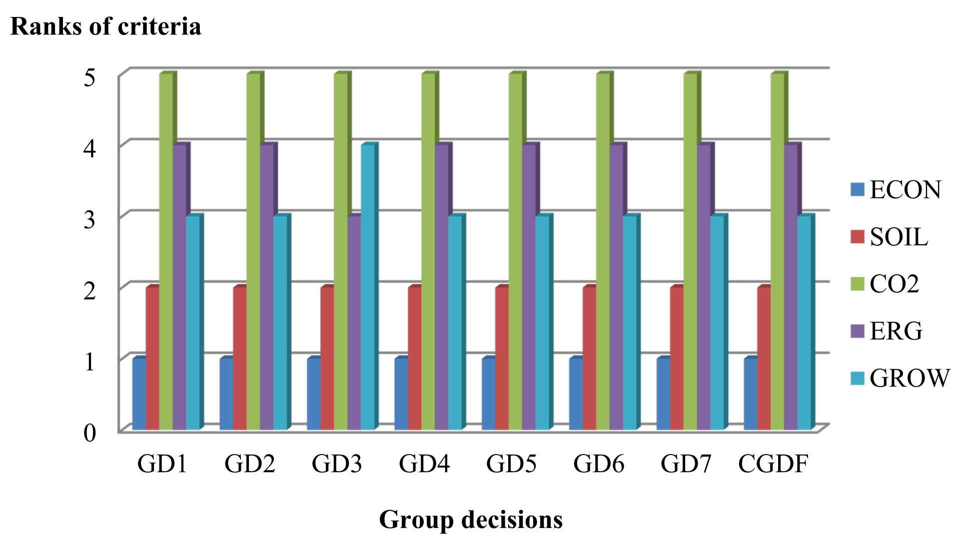

Figure 1. Ranking of criteria based on group decisions.

method used to compute the GD. However, there were three small, but distinct, differences in how the weights were allocated to criteria, depending on whether the DM weights were uniformly assigned (GD1, GD3, GD5 and GD7) or determined using ICM (GD2, GD4, GD6 and CGDF). First, in GDs where ICM is used, all criteria had the same ranking, no matter which weighting method was used (as shown in Figure 1). In contrast, when equal weights were used criterion ERG was ranked third in GD3, otherwise it was ranked fourth. Second, the inter-weights consistency metric (defined by Euclidean distance) is less for the group weightings based on ICM weightings for DMs (GD2, GD4 and GD6) than for the group weightings that assign equal weight to every DM (GD1, GD3 and GD5), as shown in Table 7. In practice, this means that differences between group weights of criteria (obtained with three different weighting methods) were lower when ICM weights of DMs were used. Third, the differences between maximum and minimum group criterion weights (max-min) and the standard deviation (SD) for a single weighting method (i.e. compare GD1 with GD2; GD3 with GD4; GD5 with GD6; and GD7 with CGDF) were always smaller when ICM weights for DMs were used (as shown last two column of Table 6). This is probably because DMs who gave more extreme and more dispersed criteria weights less consistent, meaning their criteria weights contributed less when ICM weights were used, thereby reducing their effect on the group weighting.

Finally, when we compare weights of criteria obtained by proposed CGDF (where all DMs had weights obtained by ICM and used selected weighting method) with weights obtained by GD7 (where all DMs had equal weights and used selected weighting method) we can see that in both cases criterion

Table 7. *ED* values for group decisions within same set of DMs weights.

Group decisions within same set of DMs weights	*ED*
Group decisions (GD1,GD3 and GD5) with equal weights of DMs	0.047
Group decisions (GD2, GD4 and GD6) with ICM weights of DMs	0.035

ECON was the most important with weight of 0.337 and 0.359, respectively. However, within CGDF criterion ECON was less important than within GD7. Also criteria SOIL and GROW had higher weights within CGDF (0.244 and 0.205) than within GD7 (0.239 and 0.165).

Discussion

In most of the forestry related decision-making problems it is necessary to define weights of relevant criteria which represent trade-offs between various economic, ecological, and social aspects of the analyzed problem. For that purpose we developed and demonstrated the consistency-based group decision-making framework (CGDF) that is neutral with respect to multi-criteria weighting methods, thereby enabling DMs to use more than one weighting method and then have the freedom to select the method which best reflects their individual preferences. An integral part of the framework is a novel method for defining the weights assigned to DMs – the inter-weights consistency method (ICM). The use of CGDF and ICM was illustrated by a case study of a particular decision-making problem that arises in forestry such as defining weights of criteria relevant for designing the machine-trail network for driving in the forest terrain.

In the presented case study the DIRECT method was the least selected (only the times, Table 4). This could be because the DIRECT method was the first question in the questionnaire and the DMs views about their preferences may have changed while completing the questionnaire. Another possible explanation is that in the DIRECT method all criteria weights must be considered simultaneously and with approximately the same degree of importance while in AHP and SMART methods criteria are compared in pairs, which is less cognitively demanding for DMs. The idea of pairwise comparisons could be reduced to the following common-sense rule: consider two criteria at a time if you are unable to handle more than that (Kawa and Koczkodaj 2015). In addition, note that only CGDF and GD5 (combination of SMART and equal weights of DMs) had no extreme (maximum and/or minimum) criteria values (Table 6). Conversely, GD3 (combination of AHP and equal weights) had three extreme criteria values, consistent with the results of Schoemaker and Waid (1982), Belton (1986) and Pöyhönen and Hämäläinen (2001) who found that AHP produces a larger range of weights than the other weighting methods.

We believe CGDF and ICM could be useful for most group decision-making problems, not just for forest operations problems. CGDF is comparatively simple, making it easy to use, and thus less likely to produce procedural errors and more likely to be useful in practice. Moreover, there are no guarantees that more complicated procedures will provide more accurate outputs, and in many cases, fast and frugal methods can produce results that are close to or even better than those obtained by more extensive analysis (Katsikopoulos and Fasolo 2006). In addition, ICM is relatively quick to implement and therefore suitable when there are many DMs and time constraints. These properties were very important for the presented decision-making case-study because DMs from forest industry (operator and four forest company managers) did not have too much time to dedicate to interviews – which were done during DMs working hours. However, it was very important for this problem domain – and probably for many others – to have opinions from practitioners (and not just academics) included in the decision-making process.

However, there are no guarantees that consistent preferences are correct and accurate. However, other methods for defining expertise are also affected by this problem. Garthwaite et al. (2005) conclude that in order for an elicitation process to be successful, the preferences do not need to be "true" in an objectivist sense and cannot be judged that way, but should be an accurate representation of the expert's present knowledge, regardless of the quality of that knowledge (Riabacke et al. 2012). Similarly, Noble (2004) claims that an expert may not be able to provide an accurate judgment but any DM with a clear understanding of the issue, decision variables, and the decision process should be able to demonstrate consistency in making judgments, which is critical to ensuring the quality of obtained decisions. Comparing the ranges of criteria weights (Table 5), given by the least consistent decision-maker (DM11) and the most (DM12), it seems reasonable to assign weights of 0.0260 and 0.1268, respectively, to them (Table 4). Thus, DM11's weights, despite being the least consistent, are still included in the group decision. However, the influence (DM weight) of those criteria weights is decreased from 0.0556 (equal weight assigned to each DM) to 0.0260 (ICM weights). Arguments supporting the approach used in ICM can be found in Aubert and Lienert (2019), who stated that inconsistent preferences between weighting methods suggest either that DM preferences have not yet been decided or that the DM does not know how to express those preferences with the weighting methods in use. Perhaps, it is not fair or just to decrease the weight assigned to a DM whose preferences are not expressed well with the available methods, but it is reasonable, pragmatic, and practical, especially in the situation when DMs have limited time available.

Like many methods for evaluating expertise, ICM does not attempt to equate expertise with answers to known questions because such questions and answers do not exist in many problem domains. Although ideal weights of DMs ("true" or "correct" measure of DMs' expertise) is impossible to achieve, ICM can minimize effect of random and poor answers. ICM does not necessarily assign high weights DMs with advanced knowledge, rather it assigns high weights to DMs who have already reflected on the decision problem and formed opinions. However, it is likely that DMs with advanced knowledge related to the decision-making problem will have formed such opinions. For instance, Lienert et al. (2016) found strong indications that having more knowledge and expertise about problem-related issues is correlated with higher preference stability whilst the influence of other explanatory variables remains inconclusive. It could be that DMs reflected on the decision problem, formed preferences and then over a longer period of time (e.g. one month) changed preferences for some other reasons (such as sociodemographic factors, past experience, knowledge and expertise about a topic, learning, the occurrence of externals events, the strength of preferences and the difficulty of the elicitation method), but the literature on these topics is scant and the evidence even contradictory (Lienert et al. 2016). One potential advantage of CGDF and ICM is that the time between preference elicitations with different methods is very short (less than one minute), so the effect of many of the factors listed above should be minimal.

An alternative and similar method could be to define weights of DMs by using consistency of preferences over time (rather than using different weighting methods), meaning that preferences from the same DMs will be elicited using a single weighting method on more than one occasion. This method makes sense, but is much more time-consuming than our approach because time between two interviews would need to be much longer. Also, in situations where it is necessary to assign equal weights to DMs, inter-weights consistency can be used as feedback for DMs (Aubert and Lienert 2019). This means that DMs showing high levels of inconsistency are advised to reconsider the criteria weights they have assigned. Again, this approach is more time-consuming than CGDF and according to Barzilai (1998) forcing improvements in consistency, similar to forcing consensus, should be avoided because it may distort the individual's true answer.

In summary, CGDF and ICM attempt to reduce the effect of answers from DMs whose expertise is less than that of others in the decision-making group (and increase it for those with more expertise), while being simple and quick to implement. Thus, CGDF and ICM are particularly useful when DMs and decision analysts have only limited time available for interviews and there are limited resources for analyzing the responses of DMs. In addition, several interesting observations arise from the application of CGDF and ICM to the forestry case study. The main outcome from the results section is that ICM weights of DMs made group decisions (weights assigned to criteria based on the collective weights of the DMs) less dependent on the choice of weighting method(s). This is true for the group rankings of criteria – GDs based on ICM produced same rankings (Figure 1) – and for group weights of criteria – differences between GDs obtained with three different weighting methods were lower when ICM weights of DMs were used (Table 7). This property of ICM could be especially beneficial for the decision analyst – in particular making the job of the decision analyst less complicated – because the choice of weighting method will have less impact on the group decision compared to when DMs have equal weights. Last, as noted earlier, ICM reduced the dispersions and ranges in group criteria weights for a single weighting method (last column in Table 6) compared to group decisions obtained when DMs have equal weights. Whether this is an advantage or not of ICM is unclear, but it will be important to try to find an explanation for this occurrence and thus determine whether it is an advantageous feature of ICM. In conclusion, further case studies – using real-world group decision-making problems – are required in order to better understand CGDF and ICM and hopefully confirm the positive preliminary findings described above.

Conclusions

Most aspects of forestry address complex problems that require the weights of relevant criteria – representing trade-offs between various economic, ecological and social aspects of the problem – to be defined. When addressing this in planning processes in a structured way, this is usually done by using multicriteria weighting method(s) in group (participatory) context in order to include different opinions and to minimize risk of poor individual judgments. Furthermore, in group decision-making, the weights of decision makers (DMs) must be defined.

For that purpose, we proposed the consistency-based group decision-making framework (CGDF), which uses the expertise of a decision maker (DM) to weight the responses of the DM when deriving an overall group decision. The novel part of CGDF is the inter-weights consistency method (ICM), for evaluating the expertise of a DM based on the consistency of the weights the DM assigns to different criteria using different multicriteria weighting methods. Although inconsistency in a DM's responses may not be just because of lack of expertise, it indicates that the DM is relatively unreliable and therefore, in the presented framework, the weights of less consistent DMs have lower impact on group decisions than those who are more consistent.

The presented framework has several desirable qualities. First, it is neutral with respect to multi-criteria weighting methods, thereby enabling DMs to use more than one weighting method and then have the freedom to select the method which best reflects their individual preferences. In situations where no consensus exists regarding the most valid weighting method, this is an objective and transparent procedure. Second, using several weighting methods serves as a mechanism for calculating the consistency of DMs. The presented framework is relatively simple (it is easy to prepare and analyze questionnaires) and suitable for the presented decision-making case-study when DMs from the forest industry (operators and forest company managers) do not have much time to dedicate to interviews.

Acknowledgements

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Boško Blagojević http://orcid.org/0000-0001-5962-7332
Eva-Maria Nordström http://orcid.org/0000-0002-9199-2230
Ola Lindroos http://orcid.org/0000-0002-7112-4460

References

Abdolmohammadi M, Shanteau J. 1992. Personal attributes of expert auditors. Organ Behav Hum Decis Process. 53:158–172. doi:10.1016/0749-5978(92)90060-K.

Aubert AH, Lienert J. 2019. Gamified online survey to elicit citizens' preferences and enhance learning for environmental decisions. Environ Model Softw. 111:1–12. doi:10.1016/j.envsoft.2018.09.013.

Barzilai J. 1998. Consistency measures for pairwise comparison matrices. J Multi-Criteria Decis Anal. 7:123–132. doi:10.1002/(SICI)1099-1360(199805)7:3<123:AID-MCDA181>3.0.CO;2-8.

Belton V. 1986. A comparison of the analytic hierarchy process and a simple multi-attribute value function. Eur J Oper Res. 26:7–21. doi:10.1016/0377-2217(86)90155-4.

Blagojevic B, Srdjevic B, Srdjevic Z, Zoranovic T. 2016. Heuristic aggregation of individual judgments in AHP group decision making using simulated annealing algorithm. Inf Sci. 330:260–273. doi:10.1016/j.ins.2015.10.033.

Blagojevic B, Jonsson R, Björheden R, Nordström EM, Lindroos O. 2019. Multi-Criteria Decision Analysis (MCDA) in forest operations – an Introductional Review. Croat J for Eng. 40:191–205.

Cooke RM. 1991. Experts in Uncertainty. Oxford: Oxford University Press.

Crawford G, Williams C. 1985. A note on the analysis of subjective judgment matrices. J Math Psychol. 29:387–405. doi:10.1016/0022-2496(85)90002-1.

Edwards W. 1977. How to use multiattribute utility measurement for social decision making. IEEE Trans Syst Man Cybern. 7:326–340. doi:10.1109/TSMC.1977.4309720.

Einhorn HJ. 1972. Expert measurement and mechanical combination. Organ Behav Hum Perform. 7:86–106. doi:10.1016/0030-5073(72)90009-8.

Einhorn HJ. 1974. Expert judgment: some necessary conditions and an example. J Appl Pyschol. 59:562–571. doi:10.1037/h0037164.

Eliasson L. 2005. Effects of forwarder tyre pressure on rut formation and soil compaction. Silva Fenn. 39:549–557. doi:10.14214/sf.366.

French S. 2011. Aggregating expert judgement. Revista de la Real Academia de Ciencias Exactas, Fisicas y Naturales, Serie A: Matematicas. 105:181–206. doi:10.1007/s13398-011-0018-6.

Garthwaite PH, Kadane JB, O'hagan A. 2005. Statistical methods for eliciting probability distributions. J Am Stat Assoc. 100:680–700. doi:10.1198/016214505000000105.

Gigerenzer G, Goldstein DG. 1996. Reasoning the fast and frugal way: models of bounded rationality. Psychol Rev. 103:650–669. doi:10.1037/0033-295X.103.4.650.

Hammond KR. 1996. Human Judgement and Social Policy. New York: Oxford University Press.

Heralt L. 2002. Using the roadeng system to design an optimum forest road variant aimed at the minimization of negative impacts on the natural environment. J for Sci. 48:361–365. doi:10.17221/11926-JFS.

Hoeffler S, Ariely D. 1999. Constructing stable preferences: a look into dimensions of experience and their impact on preference stability. J Consum Psychol. 8:113–139. doi:10.1207/s15327663jcp0802_01.

Holmström E, Nikander J, Backman J, Väätäinen K, Uusitalo J, Jylhä P. 2022. A multi-objective optimization strategy for timber forwarding in cut-to-length harvesting operations. Int J for Eng. 1–17. doi:10.1080/14942119.2022.2149003.

Horn R, Vossbrink J, Peth S, Becker S. 2007. Impact of modern forest vehicles on soil physical properties. For Ecol Manag. 248:56–63. doi:10.1016/j.foreco.2007.02.037.

Hosseini A, Lindroos O, Wadbro E. 2018. A holistic optimization framework for forest machine trail network design accounting for multiple objectives and machines. Can J for Res. 49:111–120. doi:10.1139/cjfr-2018-0258.

Kangas A, Kurttila M, Hujala T, Eyvindsin K, Kangas J. 2015. Decision support for forest management. Second ed. Berlin: Springer.

Katsikopoulos K, Fasolo B. 2006. New tools for decision analysts. IEEE Trans Syst Man Cybern A. 36:960–967. doi:10.1109/TSMCA.2006.871798.

Kawa A, Koczkodaj WW. 2015. Supplier evaluation process by pairwise comparisons. Math Probl Eng. 2015:1–9. doi:10.1155/2015/976742.

Keeney RL, Raiffa H. 1976. Decision analysis with multiple conflicting objectives. New York: Wiley & Sons.

Koksalmis E, Kabak Ö. 2019. Deriving decision makers' weights in group decision making: an overview of objective methods. Inf Fusion. 49:146–160. doi:10.1016/j.inffus.2018.11.009.

Kontic B. 2000. Why are some experts more credible than others? Environ Impact Assess Rev. 20:427–434. doi:10.1016/S0195-9255(00)00057-3.

Lichtenstein S, Slovic P. 2006. The Construction of Preference. Cambridge: Cambridge University Press.

Lienert J, Duygan M, Zheng J. 2016. Preference stability over time with multiple elicitation methods to support wastewater infrastructure decision-making. Eur J Oper Res. 253:746–760. doi:10.1016/j.ejor.2016.03.010.

Marchi E, Chung W, Visser R, Abbas D, Nordfjell T, Mederski PS, McEwan A, Brink M, Laschi A. 2018. Sustainable Forest Operations (SFO): a new paradigm in a changing world and climate. Sci Total Environ. 634:1385–1397. doi:10.1016/j.scitotenv.2018.04.084.

Multi-criteria analysis: a manual 2009. Department for Communities and Local Government. London, UK.

Noble BF. 2004. Strategic environmental assessment quality assurance: evaluating and improving the consistency of judgments in assessment panels. Environ Impact Assess Rev. 24:3–25. doi:10.1016/S0195-9255(03)00118-5.

Porvari P, Verta M, Munthe J, Haapanen M. 2003. Forestry practices increase mercury and methyl mercury output from boreal forest catchments. Environ Sci Technol. 37:2389–2393. doi:10.1021/es0340174.

Pöyhönen M, Hämäläinen RP. 2001. On the convergence of multiattribute weighting methods. Eur J Oper Res. 129:569–585. doi:10.1016/S0377-2217(99)00467-1.

Riabacke M, Danielson M, Ekenberg L. 2012. State-of-the-art prescriptive criteria weight elicitation. Adv Decis Sci. 2012:1–24. doi:10.1155/2012/276584.

Saaty TL. 1980. The analytical hierarchy process. New York: McGraw Hill.

Schoemaker PJ, Waid CC. 1982. An experimental comparison of different approaches to determining weights in additive utility models. Manag Sci. 28:182–196. doi:10.1287/mnsc.28.2.182.

Shanteau J, Weiss DJ, Thomas RP, Pounds JC. 2002. Performance-based assessment of expertise: how to decide if someone is an expert or not. Eur J Oper Res. 136:253–263. doi:10.1016/S0377-2217(01)00113-8.

Slovic P. 1995. The construction of preference. Am Psychol. 50:364–371. doi:10.1037/0003-066X.50.5.364.

Weiss DJ, Shanteau J. 2003. Empirical assessment of expertise. Hum Factors. 45:104–116. doi:10.1518/hfes.45.1.104.27233.

von Winterfeldt D, Edwards W. 1986. Decision analysis and behavioral research. Cambridge: Cambridge University Press.

Appendix A. Example of steps required to apply the study's results in a real-life case study

This text gives an example on how the article's weights of decision makers in group decision-making situations can be applied. In a theoretical example, the steps to determine an optimal machine trail network is provided, starting from defining criteria and ending at the objective function of a multicriteria optimization problem.

To keep the example simple and clear, only a small set of criteria is used and with hypothetical ranges. Moreover, only the steps needed to be taken is presented, so no actual solution for the problem is provided.

Step 1. Identify the criteria (i.e. objectives) used for determining an optimal machine trail network.

Three criteria are considered in this example:
Criterion 1: Length (km)
Criterion 2: Time (hours) and
Criterion 3: Soil damage risk (proportion (%) of the trail network being located on certain soils).

Step 2. Identify the ranges for each criterion

Ranges are found by single-objective optimization for each criterion. Hypothetical results of those three single-objective optimizations are presented in Table A1. The results from the three optimizations providing the minimum and maximum values of all criteria when optimizing for different criterion. Thus, the ranges for the criteria are identified (Table A2).

Table A1. Results of single-objective optimizations.

Optimization	Length (km)	Time (hours)	Soil damage (%)
1: Minimize length	0.7[a]	1.0	15
2: Minimize time	0.9	0.95[a]	20
3: Minimize soil damage risk	1.3	1.05	5[a]

Table A2. Ranges of values for criteria.

Criterion	Range (min-max)
Length (km):	0.7–1.3
Time (hour):	0.95–1.05
Soil damage risk (%):	5–20

Step 3. Normalizing the values of each criterion

In order to consider the different criteria fairly in respect to each other, despite different ranges of their respective scales, criterion values are normalized. This can be done in different ways, but a common way is to use a continuous (score) scale from 0–100, where 0 represents the worst value of each criterion and 100 represents the best value. Those worst and best values are the ranges already obtained in Step 2 (Table A2). A value function needs to be defined, to describe how a criterion value translates to the normalized scale. Any function is possible, but for simplicity here they are assumed to be linear according to Figures A1–3.

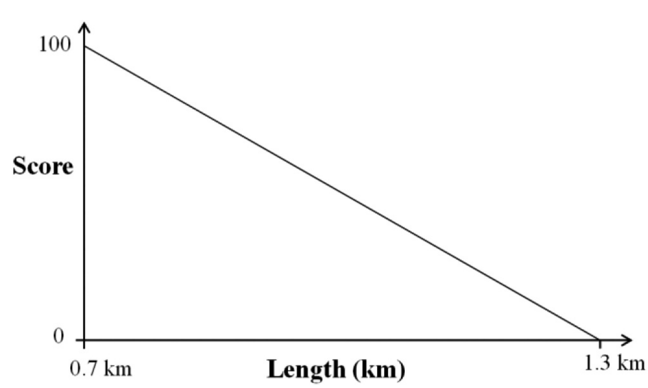

Figure A1. Value function for the hypothetical relationship between the values within the length range and the normalizing score.

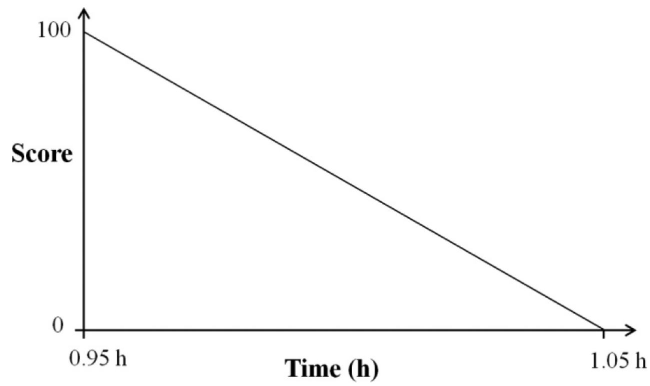

Figure A2. Value function for the hypothetical relationship between the values within the time range and the normalizing score.

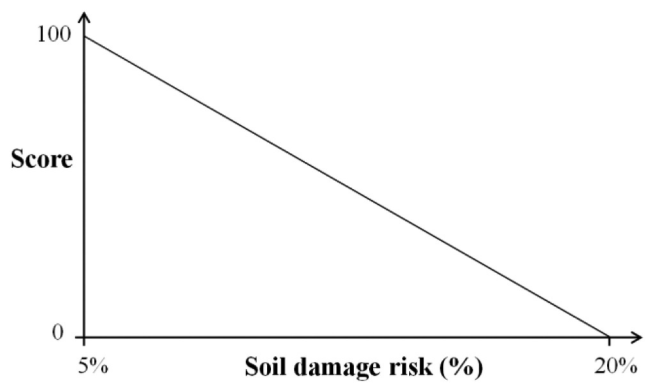

Figure A3. Value function for the hypothetical relationship between the values within the soil damage risk range and the normalizing score.

Step 4. Define weights of criteria

In this step weights for each of the criteria – reflecting their relative importance – are assigned. Usually this is done in group (participatory) context in order to include different opinions and to minimize risk of poor individual judgments. In order to do that properly and meaningfully, selected criteria with corresponding ranges (min-max) should be presented to DMs before application of multicriteria weighting methods. To define weights of criteria (or objectives) DMs are encouraged to take into account both the difference between the least and most preferred values within each criterion (here, presented in Tables A1 and A2), and how much they care about that difference.
Furthermore, in group decision making, the weights of decision makers (DMs) must be defined. For that purpose, we propose to use the consistency-based group decision-making framework (CGDF), which is described in detail in this paper. The integral part of CGDF is the inter-weights consistency method (ICM), for defining weight of a DM based on the consistency of the weights the DM assigns to different criteria using different multicriteria weighting methods.

Finally, the group weights of criteria (w^{gr}) are calculated by summing the products of the individual weights of criteria and corresponding weights of DMs. To novice users within the field of MCDA we recommend reading *Multi-criteria analysis: a manual (2009)* for more details.

Step 5. Multi-objective optimization of machine-trail network
Use criteria scores (s) from step 3 and the group weights of criteria (w^{gr}) from step 4 to create a goal function for a multi-objective optimization, which in this example would be to:

$$Maximize: w^{gr}_{length} \times s_{length} + w^{gr}_{time} \times s_{time} + w^{gr}_{soil\,damage\,risk} \times s_{soil\,damage\,risk}$$

Appendix B

Table B1. Individual weights of criteria obtained with all weighting methods and corresponding consistency measures (selected weighting method by each DM is highlighted).

			Criteria weights					
Decision makers		Methods	ECON	SOIL	CO2	ERG	GROW	*ED*
DM1	FCM	DIRECT	0.350	0.250	0.100	0.100	0.200	
		AHP	0.554	0.221	0.048	0.061	0.116	0.1723
		SMART	0.264	0.236	0.167	0.139	0.194	
DM2	FCM	DIRECT	0.300	0.400	0.100	0.100	0.100	
		AHP	0.317	0.460	0.032	0.072	0.119	0.0876
		SMART	0.231	0.385	0.077	0.115	0.192	
DM3	FCM	DIRECT	0.300	0.300	0.000[a]	0.300	0.100	
		AHP	0.175	0.369	0.039	0.341	0.076	0.0964
		SMART	0.235	0.294	0.059	0.265	0.147	
DM4	FCM	DIRECT	0.250	0.150	0.150	0.350	0.100	
		AHP	0.235	0.094	0.098	0.519	0.054	0.1003
		SMART	0.263	0.105	0.158	0.421	0.053	
DM5	CON	DIRECT	0.300	0.100	0.300[b]	0.200	0.100	
		AHP	0.385	0.049[a]	0.128	0.385	0.052	0.1836
		SMART	0.526	0.053	0.132	0.263	0.026	
DM6	PST	DIRECT	0.250	0.250	0.200	0.150	0.150	
		AHP	0.577	0.208	0.086	0.095	0.033	0.1926
		SMART	0.469	0.250	0.125	0.125	0.031	
DM7	PST	DIRECT	0.600[b]	0.150	0.100	0.100	0.005	
		AHP	0.596	0.122	0.043	0.176	0.063	0.1286
		SMART	0.455	0.273	0.091	0.136	0.045	
DM8	RES	DIRECT	0.400	0.200	0.200	0.100	0.100	
		AHP	0.511	0.308	0.050	0.059	0.073	0.1289
		SMART	0.500	0.250	0.036	0.071	0.143	
DM9	RES	DIRECT	0.400	0.100	0.250	0.100	0.150	
		AHP	0.308	0.084	0.234	0.089	0.284	0.0968
		SMART	0.410	0.128	0.205	0.051	0.205	
DM10	RES	DIRECT	0.600[b]	0.400	0.000[a]	0.000[a]	0.000[a]	
		AHP	0.506	0.326	0.028	0.044	0.096	0.2133
		SMART	0.295	0.269	0.128	0.141	0.167	
DM11	RES	DIRECT	0.265	0.206	0.235	0.147	0.147	
		AHP	0.239	0.120	0.071	0.527[b]	0.043	0.2290
		SMART	0.306	0.222	0.167	0.278	0.028	
DM12	RES	DIRECT	0.333	0.222	0.056	0.056	0.333	
		AHP	0.362	0.175	0.070	0.054	0.338	0.0469
		SMART	0.316	0.211	0.053	0.105	0.316	
DM13	RES	DIRECT	0.600[b]	0.200	0.050	0.100	0.050	
		AHP	0.486	0.287	0.032	0.077	0.117	0.100
		SMART	0.469	0.313	0.031	0.094	0.094	
DM14	RES	DIRECT	0.300	0.300	0.000[a]	0.100	0.300	
		AHP	0.259	0.475[b]	0.029	0.050	0.188	0.1204
		SMART	0.313	0.313	0.031	0.094	0.250	
DM15	RES	DIRECT	0.600[b]	0.200	0.000[a]	0.000[a]	0.200	
		AHP	0.443	0.338	0.032	0.032	0.155	0.1352
		SMART	0.400	0.320	0.040	0.040	0.200	
DM16	RES	DIRECT	0.200	0.400	0.000[a]	0.000[a]	0.400	
		AHP	0.150	0.393	0.032	0.032	0.393	0.0629
		SMART	0.213	0.426	0.021	0.021	0.319	
DM17	RES	DIRECT	0.200	0.200	0.150	0.050	0.400	
		AHP	0.180	0.221	0.084	0.040	0.474[b]	0.0703
		SMART	0.190	0.190	0.143	0.095	0.381	
DM18	RES	DIRECT	0.120	0.120	0.060	0.500	0.200	
		AHP	0.080[a]	0.088	0.037	0.521	0.274	0.1266
		SMART	0.167	0.167	0.083	0.333	0.250	

FCM: forest company manager; CON: contractor; PST: PhD student; RES: researcher; *ED*: Euclidean distance.
[a]Minimal weight of criterion; [b]maximal weight of criterion.

Questionnaire

Name: ________________________________

Company/Position: ________________________

Date and place: __________________________

Subject:

Defining weights (importance) of criteria (objectives) for forest strip-road network design

Short description of research topic: In ground based mechanized forestry, heavy machines traverse the terrain. The routes they take will here be called `strip-roads', although being unprepared terrain, and is basically created by the removal of trees and by not placing logs in it. To design a strip-road network is a complex locational problem that involves how forestry machines can operate on the terrain, in combination with trade-offs between various economic and ecological aspects. Strip-road designs are currently made manually based on intuitive decisions on the importance, correlations, and effects of the many (conflicting) aspects. However, badly designed strip-road networks could result in costly operations and adverse environmental impacts. Therefore, this study aims at presenting a holistic framework for how to determine optimal strip-road networks. Key economical and ecological objectives involved in designing road networks are presented on mechanised cut-to-length operations, with a focus on how to simultaneously address the physical capabilities and objectives of forestry machines, the impact of slope, operational costs and a simplified case of environmental impact. The results show how to mathematically formulate and combine the aspects and gives examples on how the network design changes under various inputs. However, since merely the formulation of the problem is challenging enough, future research will be needed to explore the optimal design of strip-road networks.

Description of criteria (objectives):

1. **ECON** - to minimize **Economical** costs (all possible harvesting and forwarding costs: fuel consumption, operators salaries, maintenance, etc.)
2. **SOIL** - to minimize risk of **Soil damage** – compaction and rutting (proportional to weight of the machines, number of the machine passages, soil moisture, etc.)
3. **CO2** - to minimize **CO2 emissions**
4. **ERG** - to minimize **the tilt and roll of the machines** (due to **ergonomic** reasons)
5. **GROW** - to minimize **the area with roads** (i.e. to maximize **the stand's capacity to grow** trees).

QUESTIONS:

Q1) Direct point allocation - the decision maker allocates numbers to describe the criteria weights directly. For example, decision maker is asked to divide 100 points among the attributes. It is also allowed to divide more (or less) than 100 points.

Table 1. Direct point allocation

Criteria	ECON	SOIL	CO2	ERG	GROW
Points					

Q2) AHP method – the decision maker compare all criteria in pairs using scale from Table 2.

Table 2. Importance scale

Definition	Importance
Equal importance	1
Weak dominance	3
Strong dominance	5
Demonstrated dominance	7
Absolute dominance	9
Intermediate values	(2,4,6,8)

Table 3. AHP method

Criteria	ECON	SOIL	CO2	ERG	GROW
ECON	1				
SOIL		1			
CO2			1		
ERG				1	
GROW					1

Q3) SMART method – Decision maker first rank all criteria. Then, decision maker begins with assigning 10 points to the least important (last ranked) criterion. The relative importance of the other criteria are then evaluated by giving them points from 10 upward (with no upper limit).

Table 4. SMART method

Criteria	ECON	SOIL	CO2	ERG	GROW
Rank					
Points					

Q4) Do you think that previous five criteria are relevant for forest strip-road network design?

____

Q5) Do you think there are more criteria that may be relevant for forest strip-road network design? Please write them.

____

____

____

Figure B1. Questionnaire.